Plant canopy classification methodology based on hyperspectral data cube on a polluted mining site

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1. Abstract

Canopy analysis was carried out in order to classify the differences between vegetation types at the Szárazvölgy flotation sludge reservoir. Supervised classification methods were used to distinguish 8 vegetation types based on the spectral properties of the area: forest (*Quercus sp.*), young deciduous forest, reed (*Phragmites sp.)* and aquatic plants, false indigo (*Amorpha fruticosa*), Australian pine (*Pinus nigra*), shrub – mainly sloe (*Prunus spinosa*) and dog rose (*Rosa silvestre*), blackberry (*Rubus caesius*), low biomass. The results of the classifications were compared to a ground truth image in order to know the best process for classification. The ground truth image is based on ortophoto, topographic map, and GPS based field data collection. According to results of the comparison, the parallelepiped classification method is proved to be appropriate method based on the overall accuracy of canopy classification, which was 54 % due to heterogeneity of the vegetation. The results showed that hyperspectral remote sensing is an effective tool for the characterization of canopy and monitoring of canopy changes at the examined polluted sites so that the obtained information can be a valid base for modelling soil degradation and erosion.

2. Introduction

The characterization of heavy metal polluted abandoned mining sites is a complicated assignment due to the variable spatial distribution of the pollutants, therefore complex integrated method is required in order to assess precisely the amount and the distribution of the contaminants. Several publications dealt with acid mine drainage (Szucs et al., 2002; Yan and Bradshaw, 1995) and soil plant systems for characterization of the distribution of heavy metals (Kabata-Pendias, 2001; Csathó, 1994; Kádár 1991; Faheed, 2005), but the assessment of heavy metal distribution by mapping technologies are not well studied. Many publications dealt with the successful application and the advantages of hyperspectral remote sensing (Kardeván, 2003; Burai; 2006)

Remote sensing is the science of acquiring, processing, and interpreting images and related data, acquired from aircraft and satellites, that record the interaction between matter and electromagnetic energy (Sabins, 1997). Remote sensing imagery has contributed significantly to mineral exploration. For example, mapping of geological faults and fractures that localize ore deposits and recognize hydrothermally altered rocks based on their spectral signatures (Sabins, 1999). A major problem with remote sensing approaches to mineral exploration using broad-band multispectral sensors is the insufficient spectral resolution to map hydrothermal alteration minerals**,** which exhibit subtle differences in spectral signatures (Clark, 1999).

Small bandwidths distinguish hyperspectral sensors from multispectral sensors, acquiring spectral information of materials usually over several hundreds of narrow contiguous spectral bands, with high spectral resolution on the order of 20 nm or narrower (Polder & van der Heijden, 2001). As such, they allow identification of specific materials, whereas broadband multispectral data only allow discrimination between classes of materials (Kruse et al., 2003).

Hyperspectral imagery is also appropriate for vegetation analysis. Minimum at the visible spectral range is related to pigments in plant leaves. Chlorophyll absorbs markedly spectral range between 450 – 670 nm. Reaching infrared spectral range, the reflectance of healthy vegetation increases rapidly. Healthy vegetation reflects the 40-50% of the incoming energy between 700-1300 nm spectral ranges due to the internal structure of the canopy. In this way, the measured reflectance plays an important role in distinguishing different plant species, even if these species are seems to be similar based on visible spectral range (Berke et al. 2004).

3. Methods

In this study mineral mapping and canopy analysis was also presented at the Szárazvölgy flotation sludge reservoir using ENVI 4.3 based on hyperspectral data. This area is a part of Gyöngyösoroszi abandoned Pb-Zn

mining site located in northern Hungary, where Záray (1991) reported serious heavy metal contamination.
The hyperspectral image is taken by DAIS 7915 sensor which is a 79-channel high-resolution optical airborne imaging spectrometer and collects information in five blocks of contiguous channels in the wavelength region of 0,4 to 12,3 µm. The DAIS sensor recorded spectra at SWIR I,II (1,5-1,8; 2,0-2,5), which was used for the determination of heavy-metal containing minerals, and the spectrum of VIS/NIR (0,43-1,05) was used for providing spectral information on uncovered surface and the biomass of the area.
Determination of NDVI (Normalized Difference Vegetation Index) is necessary in order to mask the location of the barren spots. In the case of vegetation analysis masking barren places and surface water is also important, because places with no vegetation disturb the supervised analysis. Values of the NDVI index are calculated from the reflected solar radiation in the near-infrared (NIR) and red (R) wavelength bands, 580-680 nm, and 730-1100 nm, respectively. NDVI can be determined using the following formula:

$$NDVI=(NIR-R)/(NIR+R).$$

Canopy analysis was carried out in order to classify the differences between vegetation types at the Szárazvölgy flotation sludge reservoir. Supervised classification and Spectral Angle Mapper (SAM) was used to distinguish 8 types of vegetation.

4. Results

First the NDVI image is defined. The area with NDVI values lower than 0,3 is found to be mainly the uncovered slopes of the mine tailings, whereas the surrounding forests, shrubs are represented with an NDVI value above 0,3 (figure 1). Based on this image, places covered by vegetation (NDVI<3) and barren places (0,3>NDVI>0) were distinguished and masked for further studies.

Figure 1 NDVI image of Szárazvölgyi reservoir

Based on the NDVI image the NDVI cross section profile of the first (Northern) reservoir (out of three) was carried out in the West- East direction (figure 2.). The water has negative NDVI value, while surrounding vegetation has markedly high values.

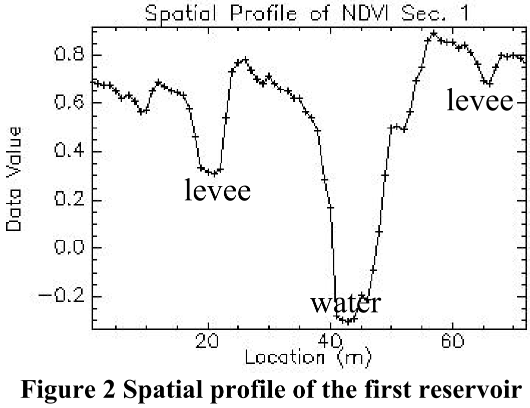

Figure 2 Spatial profile of the first reservoir

Canopy analysis was carried out in order to classify the differences between vegetation types at the Szárazvölgy

flotation sludge reservoir. Supervised classification methods were used to distinguish 8 vegetation types based on the spectral properties of the area: forest (*Quercus sp.*), young deciduous forest, reed (*Phragmites sp.)* and aquatic plants, false indigo (*Amorpha fruticosa*), Australian pine (*Pinus nigra*), shrub – mainly sloe (*Prunus spinosa*) and dog rose (*Rosa silvestre*), blackberry (*Rubus caesius*), low biomass. SAM and parallelepiped classification methods were used for classification in the case of 496 – 1300 nm, 496 – 727 és a 693 – 1300 nm spectral range. The results of the classifications were compared to a ground truth image in order to know the best process for classification. The ground truth image and training sites are based on ortophoto, topographic map, and GPS based field data collection.
Analyzing the spectral properties of the training sites, it can be stated, that some vegetation types, mainly common reed, blackberry and shrub types are sorely similar regarding their spectral features, so that in the case of classification stricter thresholds are needed to avoid inappropriate classification and overlapping between classes (figure 3).

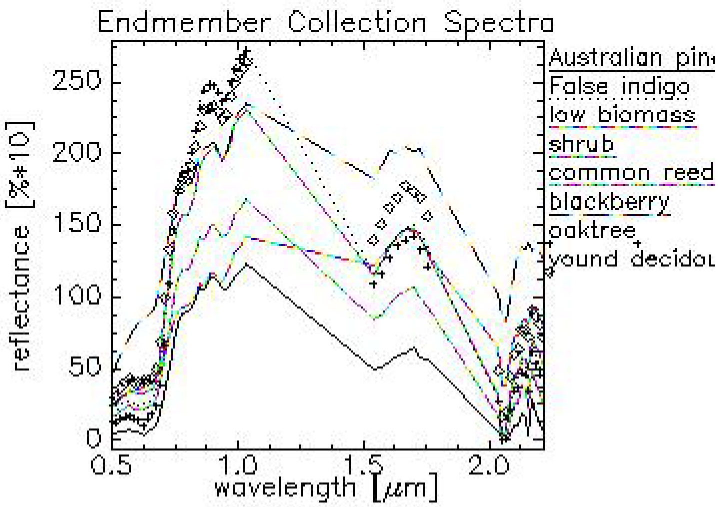

Figure 3 Reflectance curves of training sites

The accuracy of classification can be expressed by overall accuracy and Kappa index. Kappa index is more precise to evaluate the accuracy, therefore only these values are represented. Using SAM method in every (all the three) examined spectral range, only fair agreement could be achieved (table 3).

Table 3 Results of SAM for vegetation analysis

SAM	496-1300 nm	496-727 nm	693-1300 nm
K index	0,33	0,25	0,35

Using parallelepiped classification moderate agreement is achieved, especially in the case of the analysis of 496-727 nm and a 496 -1300 nm spectral range (table4.). The reason for the results is that the main differences between the spectral profiles of the training sites are shown between 500-800 nm spectral interval. Moderate agreement, result is mainly due to the heterogeneity of the vegetation at the examined site, since, despite agricultural sites, non of the classified vegetation types are homogeneous because of the natural or near natural circumstances, so other plant species and other class species are present to some extent at the one classified sites regarding for one type of vegetation..

Table 4 Results of parallelepiped classification for vegetation analysis

Parallelepiped	496-1300 nm	496-727 nm	693-1300 nm
K index	0,46	0,51	0,42

At the same time Kappa index represent the whole classification accuracy but not the accuracies of classification of each classes. In order to solve this problem two kinds of accuracy indices, producer accuracy index and user accuracy index were used to measure the classification accuracy of one class. Producer accuracy is the probability that a pixel in the classification image is put into class x given the ground truth class is x. User Accuracy is the probability that the ground truth class is x given a pixel is put into class x in the classification image. Analyzing the producer and user accuracy of the classification using 496-727 nm spectral range, the classification resulted good, very good agreements in the case of Australian pine, forest mainly oak tree, shrub sites because of their stronger homogeneity more closed canopy, and lack of other vegetation disturbance (table

5.).

Table 5 Results of classification for each group

Classes	Producer accuracy %	User accuracy %
Australian pine	66,54	99,45
False indigo	43,73	50,44
Low biomass	67,98	47,30
Shrub	69	47,04
Common reed	51,08	20,09
Blackberries	54,02	89,68
Oak forest	71,35	91,91
Young deciduous forest	44,22	42,39

5. References

Burai P.: 2006. Földhasználat-elemzés és növény-monitoring különböző adattartalmú és térbeli felbontású távérzékelt felvételek alapján. *Agrártudományi Közlemények* **22**, 7-12 pp.

Csathó P.:1994. A környezet nehézfém szennyezettsége és az agrártermelés. RISSAC,1-176pp.

Faheed F. A.: 2005. Effect of lead stress on the growth and metabolism of *Eruca sativa* M. seedlings - Acta Agronomica Hungarica, vol. 53, No 3 pp. 319 – 327pp.

Csathó P.:1994. A környezet nehézfém szennyezettsége és az agrártermelés. RISSAC,1-176pp.

Kabata-Pendias A.: 2001. Trace Elements in Soils and Plants – Third Edition. CRC Press, Boca Raton, FL.

Kádár I.: 1991. A talajok és növények nehézfémtartalmának vizsgálata. Ed: Ligetiné Nechai, E., KTM-MTA TAKI, Budapest, 104 pp.

Kardeván P. – Vekerdy Z. – Róth L. – Sommer ST. – Kemper TH. – Jordan GY. – Tamás J. – Pechmann I. – Kovács E. – Hargitai H. – László F.: 2003. Outline of scientific aims and data processing status of the first Hungarian hyperspectral data acquisition flight campaign, HYSENS 2002 HUNGARY. *3rd EARSEL Workshop on imaging spectroscopy,*324-332 pp.

Szucs A. – Jordan G. – Qvarfort U.: 2002. Geochemical modelling of acid mine drainage impact on wetland stream using landscape geochemistry, GIS and statistical methods. In: Fabbri, A.G., Gaal, G., McCammon, R.B.: Deposit and Geoenvironmental Models for Resource Exploitation an Environmental Security NATO Science Series, 2. Environmental Security. *Kluwer Academic Publishers* **80**, 425-460 pp.

Yan G. – Bradshaw A.D.: 1995. The containment of toxic wastes: II. Metal movement in leachate and drainage at Parc Lead-Zinc Mine, North Wales, Environmental Pollution, 90(3), 379-382 pp.

Záray GY.: 1991. Environmental assessment of the impact of mine tailing dumps in the valley of Toka-stream – case-study (in Hungarian) ELTE TTK Department of inorganic and analytical chemistry 1-86 pp.

Kruse, J.W. Boardman and J.F. Huntington 2003.:, Comparison of airborne hyperspectral data and EO-1 hyperion for mineral mapping, *IEEE Transactions on Geoscience and Remote Sensing* **41** (2003) (6), pp. 1388–1400.

Sabins, F.F. 1999: Remote sensing for mineral exploration, *Ore Geology Reviews* **14** (1999) (Issues 3–4), pp. 157–183.

Sabins, F.F., 1997. Remote Sensing — Principles and Interpretation, 3rd edn., W.H. Freeman, New York, NY., 494 pp.

Clark, 1999: Spectroscopy of rocks and minerals**,** and principles of spectroscopy. In: A. Rencz, Editor, *Remote sensing for the earth sciences: Manual of remote sensing* **vol. 3**, John Wiley and Sons, New York (1999), pp. 3–58 chapter 1

Polder, G. - G.W.A.M. van der Heijden, (2001): Multispectral and hyperspectral image acquisition and processing. In: Q. Tong, Y. Zhu and Z. Zhu, Editors, Proceedings of SPIE 4548.

Berke, J. - Kelemen, D. - Szabó, J. (2004): Digitális képfeldolgozás és alkalmazásai. PICTRON Kft., Keszthely